A Novel Explainable and Health-aware Food Recommender System

Merhrdad Rostami[1][a], Vahid Farahi[1,2][b], Kamal Berahmand[3][c], Saman Forouzandeh[4][d],
Sajad Ahmadian[5][e] and Mourad Oussalah[1,2][f]

[1]*Center for Machine Vision and Signal Analysis (CMVS), University of Oulu, Finland*
[2]*Research Unit of Unit of Medical Imaging, Physics and Technology, University of Oulu, Finland*
[3]*School of Computer Sciences, Queensland University of Technology, Australia*
[4]*School of Mathematics and Statistics, Faculty of Science, University of New South Wales (UNSW), Australia*
[5]*Faculty of Information Technology, Kermanshah University of Technology, Iran, Islamic Republic of*

Keywords: Food Recommender System, Healthy Recommendation, Explainability, Time-aware Recommendation.

Abstract: Food recommendation systems are increasingly being used by online food services to make recommendations. Health factors are often ignored in most of these systems, despite the fact that unhealthy diets are connected to a wide range of non-communicable diseases. Furthermore, if users do not receive compelling explanations about the recommended healthy foods, they may become hesitant to try them. In this paper, a novel explainable and health-aware food recommender system is developed to address these challenges. For this purpose, user's preferences and food health factors are taken into account simultaneously and then a rule-based mechanism is employed for final healthy and explainable recommendations. Five performance metrics were used to compare our system with different new recommender systems. Using a dataset crawled from "Allrecipes.com", the proposed model is shown to perform best.

1 INTRODUCTION

The rapid development of online food services yielded several prototypes of food recommendation systems that can assist users in finding appropriate foods according to their preferences (Shaikh et al., 2022; Ghosh et al., 2021). Despite the fact that previous food recommendations achieved acceptable efficiency in terms of learning user's preferences by mapping historical interactions with foods, these models still suffer from two significant limitations. The first one is associated with the multi-objective nature of healthy food recommendation. Recommending foods based on a target user's diet preferences and healthy food recommendations are two of the main objectives of a healthy food recommender system. In many cases, these two goals are in conflict with each other, and maximizing one of these two objectives may hurt the second objective. The second major limitation/challenge of food recommender systems is the lack of explainability and transparency. People may be reluctant to try healthy foods as well as discouraged to follow the recommendations if they do not receive compelling explanations for the healthy food recommendations they receive. For this reason, a real and efficient healthy food recommendation is one that explains to each user why the food was recommended for him/her or why another unhealthy food that may be more appropriate for his/her preferences was not recommended. We have addressed the above-mentioned limitations in this paper by developing a novel food recommender system based on health-aware multi-objective function and explainable/controllable recommendation. In comparison to previously developed food recommendation systems, the developed system makes significant contributions, which are outlined below.

- **Multi-objective:** By integrating health and nutrition factors into the food recommendation framework, this study guides users toward a healthy eat-

[a] https://orcid.org/0000-0001-5710-217X
[b] https://orcid.org/0000-0001-8355-8488
[c] https://orcid.org/0000-0003-4459-0703
[d] https://orcid.org/0000-0002-5952-156X
[e] https://orcid.org/0000-0001-8355-8488
[f] https://orcid.org/0000-0002-4422-8723

Rostami, M., Farahi, V., Berahmand, K., Forouzandeh, S., Ahmadian, S. and Oussalah, M.
A Novel Explainable and Health-aware Food Recommender System.
DOI: 10.5220/0011561700003335
In *Proceedings of the 14th International Joint Conference on Knowledge Discovery, Knowledge Engineering and Knowledge Management (IC3K 2022) - Volume 3: KMIS*, pages 208-215
ISBN: 978-989-758-614-9; ISSN: 2184-3228

ing style. The study incorporates a multi-objective measure to consider user preferences and health simultaneously.

- **Explainable Food:** An effective explainable food recommender system is introduced in this study. To the best of our knowledge, this is the first explainable food recommender systems.
- **Controllable:** A novel controllable food recommender system is developed that will enable the target user to take part in the recommendation process and strike a balance between the target users' own preferences and the health of the food.
- **Time and Ingredients-aware Similarity:** A novel ingredient and time-aware similarity measure is introduced to consider food contents and the temporal information of ratings in user similarity calculation.
- **Dynamic Neighbor Selection:** In this paper, Contrary to the previous recommender system (Ahmadian et al., 2022b; Ahmadian et al., 2022a), by incorporating the "friend of a friend" idea, a novel dynamic transitive-based nearest neighbor selection is developed.

The rest of this paper is organized as follows. We review the related works in Section 2. The developed recommender system is represented in Section 3. Experimental results are provided in Section 4. Finally, Section 5 provide the conclusion.

2 LITERATURE REVIEW

This section reviews the previous food recommendation models. Then these proposed models, their shortcomings, and drawbacks are investigated.

In (Gao et al., 2022) a food recommendation using a Graph Convolutional Network (FGCN), which uses several embedding propagation layers to model high-order connections and improve representation learning is developed. In (Gao et al., 2019), a novel hierarchical attention-based food recommender system is developed that takes into account user history about nutrition, ingredients of a food. In (Asani et al., 2021), a method for extracting customer food preferences from online restaurant reviews is developed. Their method uses NLP techniques to process the text of user comments and extract appropriate food-related terminology. The authors of (Shabanabegum et al., 2020) developed a new model to suggest different foods to the users based on the available food items in the refrigerator.

Additionally to learning user preferences, a number of previous food recommendation systems consider health issues and nutritional requirements. Elsweiler et al. (Elsweiler et al., 2017) presented a novel system for healthy food recommendation using identifying the ingredients of the foods that received a high score from the users. Bianchini et al. (Bianchini et al., 2017) developed a novel method to personalize the menu of food orders. In (Chen et al., 2020), the authors presented a novel framework called NutRec that provides a guide to healthy eating. Furthermore, in (Forouzandeh and Aghdam, 2019), considering the behavior and lifestyle of users and their nutrition, a health recommender system is presented and it provides recommendations for maintaining health. Meng et al. (Meng et al., 2020) proposed a privileged-channel infused network (PiNet) framework in a heterogeneous graph. This recommender system helps users maintain a healthy diet by creating nutritional memories. In another study (Wang et al., 2021), the authors presented Market2Dish, a personalized health-aware food recommendation scheme that can identify each food's ingredients and determine the impact of nutrition on users' health.

3 DEVELOPED SYSTEM

This section details the developed method as a novel Explainable and Health-aware Food Recommender System (in short, EHFRS), which is organized in five main steps: (1) Time- and Ingredient-aware User Similarity Calculation, (2) Neighbor Selection, (3) Initial User-Preference Prediction, (4) Food Health Factor Calculation, (5) Multi-Objective and Controllable Food Rating and (6) Explainable Food Recommendation. In the first step, a new time-aware user similarity measure is introduced based on the ingredients of rated foods by each user. A new dynamic neighbor selection mechanism is developed in the second step. In the third step, the initial user-preference for each food is predicted, while in the fourth step, the health factor is evaluated for each food item considering the ideal range of dietary factors suggested by WHO. In the fifth step, based on user-preference and estimated health factor, a new multi-objective and controllable food rating function is introduced. Finally, in the sixth step, the top healthy preferred foods along with the explanations are recommended to the target user. Figure 1 illustrates the general schema of the developed EHFRS system. The details of the proposed system are described in the following subsections.

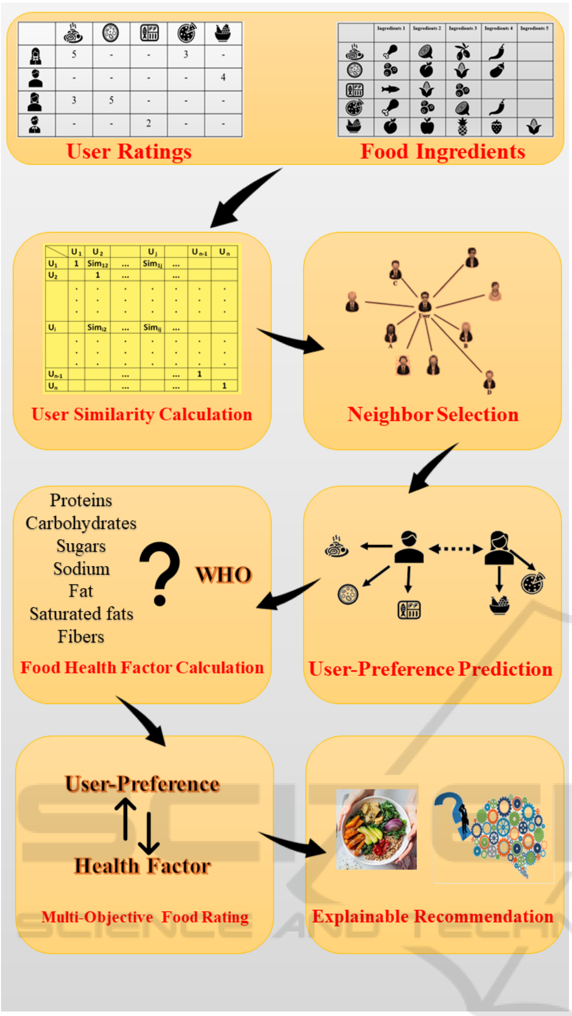

Figure 1: Overall schema of the developed EHFRS.

3.1 User Similarity Calculation

Most previous recommender systems rely mainly on direct user ratings to calculate user similarity. When such a system contains many items, while only a small number of these items have been rated by each user, the system accuracy becomes greatly reduced. This is especially true for food social networks where different types of recipes are shared for each food item, which renders the user-food matrix is very sparse. To illustrate the inefficiency of the previous similarity calculation measure, we provide an example in Figure 2. In this example, food f_1 and food f_2 were rated 5 and 4, respectively, by user u_1. On the other hand, user u_2 has rated 4 and 5 ranks to food f_3 and food f_4, correspondingly. It is apparent, at first glance, that foods f_1 and f_3 as well as f_1 and f_3 are very similar and differ only in one ingredient. Although users u_1 and u_2 have similar diet tastes and

Figure 2: Simple example of user-ingredient interaction.

preferences, by traditional similarity calculation measures, their similarity will be calculated as 0, since these users have not rated a common food.

In addition, each user's food preferences may change over time, so the voting time recorded by each user must also be taken into account. Therefore, the user similarity criterion will handle the importance of time for different ratings where the old ratings will have a lower importance than the new ratings. To defeat this issue, a novel time- and ingredient-aware measure is developed to calculate user similarities. For this purpose, the time weight of users' u_i and u_j ratings to food f_i is defined by considering the time stamp of those ratings. This time weight is determined as follows:

$$TW(u,v,f_i) = \sqrt{e^{-\lambda(TP-t(u,f_i))} \times e^{-\lambda(TP-t(v,f_i))}}. \quad (1)$$

where, $t(u, f_i)$ denotes the time period of the registered rate of user u to food f_i, TP indicates the maximum Time Period, and λ denotes a user control parameter that adjusts the impact of the time factor. A high (resp. low) value of λ indicates a greater (resp. smaller) impact of time factor in calculating similarity values. According to the user's time intervals, the ratings are divided into different time periods. For the context of our experiment detailed in the experiment section, since the collected ratings span over a period of 18 years, we divided the user ratings into monthly intervals for our experiments. In the case of more dense user ratings, weekly or even daily time frames are potential alternatives. Moreover, considering the list of ingredients of each food, the similarity between food f_i and food f_j is calculated as below:

$$SimF(f_i, f_j) = \frac{\sum_{k=1}^{K} \left(\mathrm{ing}_{ik} \times \mathrm{ing}_{jk}\right)}{Max\left(\sum_{k=1}^{K} \mathrm{ing}_{ik}, \sum_{k=1}^{K} \mathrm{ing}_{jk}\right)}. \quad (2)$$

where ing_{ik} is an indicator variable indicating to the availability of ingredient k in food f_i; namely, if food

f_i contains ingredient k, ing_{ik} will be set to 1, otherwise, $\text{ing}_{ik} = 0$. After calculating the time weight and food similarities, the user similarity $sim(u,v)$ between user u and user v is calculated as below:

$$Sim(u,v) = \frac{a}{bc} \tag{3}$$

where

$$\begin{cases} a = \sum_{f_i \in F} \sum_{f_j \in F} \left(\left(r_i(u) - \bar{r}(u) \right) \times \left(r_j(v) - \bar{r}(v) \right) \times SimF(f_i, f_j) \times TW(u,v,f_i) \right), \\ b = \sqrt{\sum_{f_i \in F} (r_i(u) - \bar{r}(u))^2 \times SimF(f_i, f_j) \times TW(u,v,f_i)}, \\ c = \sqrt{\sum_{f_j \in F} (r_j(u) - \bar{r}(u))^2 \times SimF(f_i, f_j) \times TW(u,v,f_j)}. \end{cases}$$

where $r_i(u)$ is the rating given to food f_i by user u, and $\bar{r}(u)$ is the average rating given by user u, and F is the set of initial foods in the system. Moreover, $TW(u,v,f_i)$ and $SimF(f_i, f_j)$ denote the Weight Time of the ratings of users' rates u and v for food f_i and Food similarity between Food f_i and f_j, correspondingly, calculated using Eq. 1 and Eq. 2, respectively.

3.2 Neighbor Selection

The collaborative filtering-based recommender systems' primary objective is to identify nearest neighbors through the rating prediction process and to calculate the final recommendations. Due to data sparsity of the user rating data, finding neighbors in a normal way may produce inefficient information. Therefore, in this study, a transitive-based nearest neighbor selection is developed. By combining the "friend of a friend" idea, we developed a new method for nearest neighbor selection, which includes all k-order nearest neighbors. In this proposed method, (k-1)-order neighbors will be used to calculate k-order neighbors. Our method incrementally expands neighbors, which would prepares reliable neighborhood knowledge for the final recommendation.

Let N^1_{u,f_i} be a set of users that have rated food f_i. Then, the k-order nearest neighbors of user u for the food f_i is calculated as follows:

$$N^k_{u,f_i} = \left\{ N^{k-1}_{u,f_i} \cup Neighbors(u) \right\}. \tag{4}$$

where $Neighbors(u)$ is defined as below:

$$Neighbors(u) = \{ w \in U : Sim(u,w) > \theta \}. \tag{5}$$

where, $Sim(u,w)$ indicates the user similarity between user u and w computed using Eq 3, U is the set of all users in the system, and θ is a threshold parameter for neighbors' selection. Finally, the k-order nearest neighbors of user u (regardless of the food item) is calculated by taking into account all food items as follows:

$$SumN(u)^k = \bigcup_{f_i \in F} N^k_{u,f_i}. \tag{6}$$

3.3 Initial User-preference Prediction

In this step, the users' neighbors selected are utilized to predict the food preferences of users. Let N^k_{u,f_i} be a set of k-order nearest neighbors of user u for food f_i. Then, the predicted rating $P_i(u)$ of an unknown food f_i for user u is given as follows:

$$P_i(u) = \bar{r}_u + \frac{\sum_{v \in N^k_{u,f_i}} Sim(u,v) \times (r_{v,i} - \bar{r}_v)}{\sum_{v \in N^k_{u,f_i}} Sim(u,v)}. \tag{7}$$

where $\bar{r}_u$ corresponds to the average ratings assigned by user u, $r_{v,i}$ is the rating of food f_i assigned by user v, and $Sim(u,v)$ refers to the similarity score between users u and v calculated using Eq 3.

3.4 Food Health Factor Calculation

Food recommendation systems are more critical than recommendation systems associated to movie, music or book because of the user's health impact of the underlined recommendation. Accordingly, assessing *how healthy the recommendation is* is critical in the creation of efficient food recommendation where healthy diets are significant in preventing and treating chronic diseases. Furthermore, several expert groups have recognized that diet is a critical contributor to noncommunicable disease etiology, highlighting the need to change eating habits (Organization et al., 2014). WHO has encouraged the use of nutrient profiling tools to encourage healthy diet and reduce the burden of non-communicable diseases (Lawlor and Pearce, 2013). Therefore, we have used the amount of macro-nutrients as a performance metric to assess the *health factor* of a given food. This factor evaluates the amount of seven types of nutrition categories including proteins, carbohydrates, sugars, sodium, fat, saturated fats, and fibers as per WHO suggestion. WHO provided an appropriate range for each of these nutrition categories, so that the food is deemed healthy if the amount of each category fails withing the provided range (Table 1) (Organization et al., 2007). Using the WHO ideal range, the Health Factor of food f_i can be defined as follows:

$$\begin{aligned} HF(f_i) &= Pro(f_i) + Carb(f_i) + Sug(f_i) \\ &+ Sod(f_i) + Fat(f_i) + Sat(f_i) + Fib(f_i). \end{aligned} \tag{8}$$

where $Pro(f_i)$, $Carb(f_i)$, $Sug(f_i)$, $Sod(f_i)$, $Fat(f_i)$, $Sat(f_i)$ and $Fib(f_i)$ indicate proteins, carbohydrates, sugars, sodium, fat, saturated fats, and fibers of food f_i are in ideal range or not, respectively. For example, $Pro(f_i) = 1$ if the amount of the protein in food f_i is in the ideal range shown in Table 1, otherwise; $Pro(f_i) = 0$. Therefore, it can be concluded that the value of $HF(f_i)$ is in the range of $[0\,(unhealthy),\ 7\,(healthy)]$.

Table 1: Ideal ranges of nutrition(Organization et al., 2007).

Dietary factor	Ideal Range
Proteins	10-15%
Carbohydrates	55-75 %
Sugars	<10 %
Sodium	<5 g
Fats	15-30%
Saturated fats	<10 %
Fibers	>10 g

3.5 Multi-objective Food Rating

An efficient and healthy food recommender system must consider the food recommendation as a multi-objective problem by balancing quality metrics such as the preferences of users and the health factor.

After predicting the user preferences and healthy factor of the foods, the final rating of food f_i for user u can be predicted as follows:

$$FP_i(u) = (1-\gamma).P_i(u) + \gamma.HF(f_i) \ . \tag{9}$$

where $P_i(u)$ is the predicted user preference of user u for food f_i calculated using Eq. (7), $HF(f_i)$ is Healthy Factor content of food f_i calculated using Eq. (8). While the parameter γ balances between user preference objective and the health factor objective. This parameter ranges from 0 to 1. With a higher γ parameter, food health objective becomes more significant in the final recommendation. The ability to give users control over a multi-objective recommender system allows the users to have an direct effect on the final recommendations, i.e., they can filter or re-sort the recommendations based on their preferences and healthy factor of foods. Typically, an interactive visualization framework is necessary to support user interaction during the recommendation process. This controllable parameter will allow users to participate in the final food recommender system by deciding which of these two goals (i.e., preference and healthy) is most important to them. In other words, by providing a user parameter, i.e., adjusting the health factor parameter, our controllable food recommender system lets end-users become part of the food recommendation process.

3.6 Explainable Food Recommendation

Users usually have little understanding of how the system comes up with healthy recommendations, so the reasons for receiving them remain opaque. The aim of this paper is to propose an explainable healthy food recommendation system that can explain why some unhealthy foods are not recommended and some healthy foods are. Explainable recommender systems may either be incorporated as part of their inherent design (intrinsic explainability) or provided as a post-doc explainable addition to the recommender systems(Rostami and Oussalah, 2022b; Rostami and Oussalah, 2022a). A new explainable rule mining model is developed for the final food recommendations in this step. During this step, the aim is to determine the rules in the form of $f_i \rightarrow f_j$, meaning that if a user has previously tasted (or liked) food f_i, he/she will also be interested in food f_j. In order to identify these rules, selected neighbors for each user and multi-objective food ratings are considered. For this purpose, let F_u be the set of foods rated by the target user u and let F_{N_u} be the set of foods rated by nearest neighbors of the user u. Next, the set of foods rated by all the users in $SumN(u)^k$ except the target user u, which has not rated them yet, is defined as below:

$$F'_u = F_{SumN(u)^k} - (F_u \cap F_{SumN(u)^k}). \tag{10}$$

Then, for each food $f_i \in F_u$ and each food $f_j \in F'_u$ the confidence value of rule $f_i \rightarrow f_j$ can be calculated using the following equation:

$$conf\,(f_i \rightarrow f_j) = \frac{n(f_i, f_j)}{n(f_i)}. \tag{11}$$

where $n(f_i)$ is the number of users in $SumN(u)^k$ who have rated food f_i, and $n(f_i, f_j)$ is the number of users in $SumN(u)^k$ who have rated both food f_i and f_j.

Then, the preference rank of food $f_j \in F'_u$ for the target user u is calculated as follows:

$$PrefRank_j(u) = \arg\max_{f_i \in F_u}(conf\,(f_i \rightarrow f_j) \times P_j(u)). \tag{12}$$

where $P_j(u)$ indicates the predicted rating of food f_j for user u calculated using Eq. (7).

Accordingly, the healthy-preference rank of food $f_j \in F'_u$ for target user u is defined as below:

$$HealthPrefRank_j(u) = \arg\max_{f_i \in F_u}(conf\,(i \rightarrow j) \times FP_j(u)). \tag{13}$$

where $FP_j(u)$ is the final healthy and preference rating of food f_j for user u calculated using Eq. (9).

Then, according to the obtained preference rank and healthy-preference rank of foods, we can identify the preference and healthy-preference foods. Let the Preference Food set of user u be $PrefF(u)$, where unseen foods for user u are the Top-L highest $PrefRank_j(u)$ based on Eq 12. Moreover, the healthy-preference food set of user u, $HealthF(u)$ are the Top-L highest ranks $HealthPrefRank_j(u)$ according to Eq 13. Therefore, the set of Unhealthy and

Preference foods for user u can be calculated as follows:

$$UP(u) = \{f \in F | f \in PrefF(u) \wedge f \notin HealthF(u)\}. \quad (14)$$

The set of Unhealthy and Preference foods for user u $UP(u)$ will be introduced to the target user with this explanation:

While these foods may be your favorites, they are not recommended due to their unhealthy content.

Moreover, for each food in the $HealthF(u)$ food set, considering the rules $(f_i \rightarrow f_j)$ according to Eq 13 that leads to this recommendation where the following explanation is displayed to the user:

This food is also of interest to users who have liked food f_i.

4 EXPERIMENTAL RESULTS

We conducted extensive experiments to assess the effectiveness of the developed EHFRS. As part of the evaluation of our model, we crawled the www.Allrecipes.com food social network, and extracted 52,821 foods for the period 2000-2018. Users' ratings, food nutrition, and timestamps are crawled for each food (Gao et al., 2019). The rating of a variety of foods is used to generate an implicit feedback, denoting whether the users interacted with food items. Totally, 68,768 users, 45,630 food items and 1,093,845 ratings were obtained.

In order to assess the effectiveness of the developed food recommender system, five well-known metrics have been utilized, including Precision, Recall, F1, AUC, and NDCG. There is no straightforward way to evaluate the precision and recall of recommender systems because each item needs to be rated by the user to determine if it is relevant. To this end, in our experiments, we employ Precision@N, Recall@N, and F1@N (N=size of the recommendation list).

4.1 Experimental Setup

The developed EHFRS model has four input parameters, which their values should be initialized before performing the experiments. The first parameter is λ, which specifies the importance of time factor in calculating time-aware similarity values (Eq. (1)). The parameter of k is the second parameter that denotes the order of order nearest neighbors in neighbor selection step (Eq. (4)). Moreover, θ is the third parameter and used in the neighbor definition formula (Eq. (5)). Finally, γ is the fourth parameter to balance between

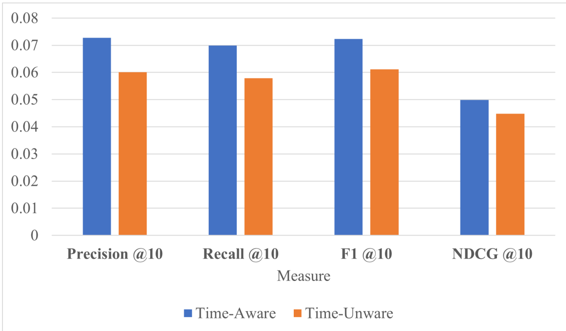

Figure 3: Performance analysis of Time factor.

user preference objective and the health factor objective (Eq. (9)). Accordingly, the values of λ, k and θ parameters are set to 4, 0.6 and 3, respectively. Moreover, the sensitivity analysis of γ parameter is shown in further experiments.

4.2 Performance Comparison

We conduct extensive experiments to verify the effectiveness of the developed EHFRS model. We then report the results and discuss them using various aforementioned evaluation metrics. In order to make a comparison, four state-of-the-art food recommendation approaches including Hierarchical Attention Food Recommendation (HAFR) (Gao et al., 2019), Collaborative Filtering Recipe Recommendations (CFRR) (Chavan et al., 2021), Heterogeneous Recipe Graph Recommendation model(HGAT) (Tian et al., 2021) and Food recommendation with Graph Convolutional Network (FGCN) (Gao et al., 2022) are chosen as baselines.

In the first part of our experiments, we will investigate the effect of taking timestamps into account when predicting user rates by our developed food recommender system. Figure 3 evaluates the efficiency of the proposed food recommendation with and without taking the timestamps into account when recommendation process. As shown in this figure, the developed time-aware food recommender system predicts ratings substantially better than its time-unaware counterpart. For example, Precision@10, Recall@10, F1@10 and NDCG@10 improved by 21,13%, 20.72%, 18.13% and 11.38, respectively.

In the next experiment, the different food recommender systems are compared in terms of Precision@10, Recall@10, F1@10, AUC and NDCG@10. Table 2, shows the performance of different food recommender systems. The developed food recommendation model (i.e., EHFRS) outperformed all other state-of-the-art models based on all of the evaluation metrics. Moreover, the study of these results

Table 2: Performance of compared food recommendations.

Method	Precision	Recall	F1	AUC	NDCG
HAFR	0.0692	0.0671	0.0687	0.6439	0.0451
CFRR	0.0671	0.0647	0.0637	0.6421	0.0431
HGAT	0.0672	0.0649	0.0638	0.6431	0.0436
FGCN	0.0710	0.0681	0.0695	0.6639	0.0462
EHFRS	**0.0739**	**0.0703**	**0.0717**	**0.6884**	**0.0512**

reveals that the proposed method is 4.08%, 3.23%, 3.16%, 3.69% and 10.82% more efficient than the second-best food recommender system (i.e., FGCN) in terms of Precision@10, Recall@10, F1@10, AUC and NDCG@10 metrics, respectively. It should be noted that in this experiment the γ parameter of the developed EHFRS that controls the food healthy factor's of recommendations is set to 0.2.

The next experiments investigate the effects of changing the size of the recommendation list on the different metrics. The experiments examined the performance of the different food recommender systems when the recommendation list sizes were 10, 15, and 20. Figures 4 - 6 illustrate the effects of the size of the recommendation list on Precision, Recall, and NDCG metrics. It was found that increasing the size of the recommendation list increases Recall and NDCG

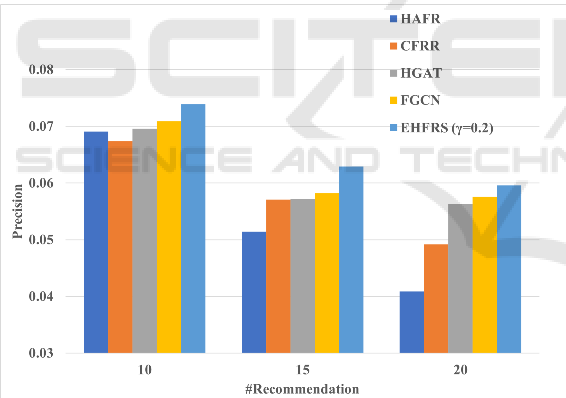

Figure 4: Precision of Top-N recommended foods.

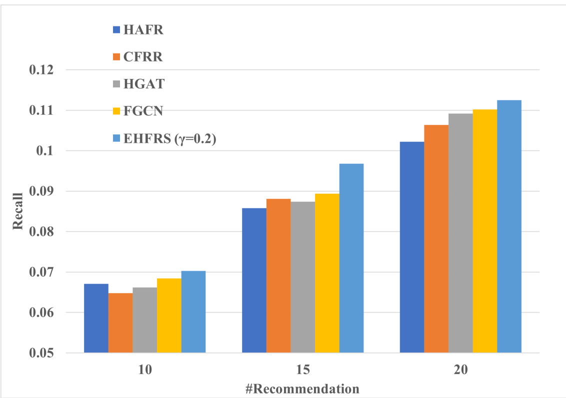

Figure 5: Recall of Top-N recommended foods.

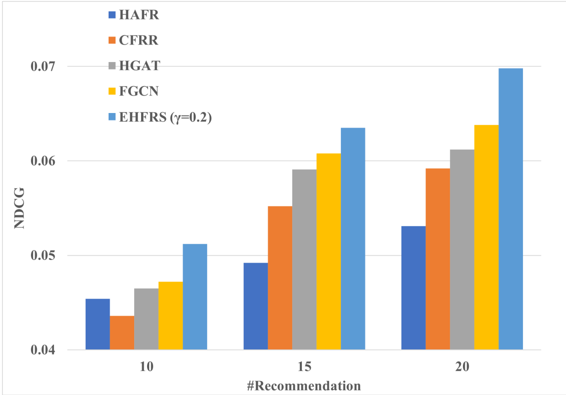

Figure 6: NDCG of Top-N recommended foods.

metrics and reduces Precision. Furthermore, the reported results in these experiments demonstrated that the developed food recommender system consistently outperformed other compared systems.

The health controllable parameter of γ, which determines how much healthy factor of foods is considered in the final recommendations, is one of the most important parameters of the developed food recommender system. A user can adjust this parameter based on how important the health of the food is to him/her. It is clear that the more this parameter is set to a high value, the more important the food health will be in the food recommendation process, and as a result, these recommendations will be further away from the user's preferences. In fact, setting this parameter to a high value can reduce the classic metrics of the recommender system, including Precision, Recall, F1, and NDCG. In Figure 7, the effect of γ parameter, when it increases from 0 to 0.8, on the different recommended systems metrics is investigated. As the results show, changing the Delta parameter from zero to 0.8 reduced the Precision@10, Recall@10, F1@10, and NDCG@10 metrics by about 52.02%, 37.73%, 45.58% and 40.09%, respectively.

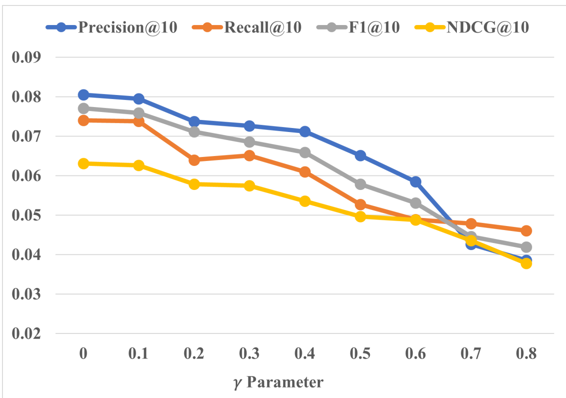

Figure 7: Performance evaluation of the health factor.

5 CONCLUSION

The use of food recommendation systems has significantly increased in online food services in recent years, aiming at providing users with personalized food recommendations. In this paper, a novel explainable and health-aware food recommender system is developed and its performance is investigated on the real-world food social network. In terms of Precision, Recall, F1, AUC, and NDCG, the developed EHFRS performed significantly better than state-of-the-art food recommendation models.

In addition, traditional food recommendation models generally focus on single-user scenarios, however, most real-life interactions take place in groups, In future, we plan to developed food group recommendation models. In addition, in future, we aim to enhance the performance of the food recommendation by incorporating additional user information.

ACKNOWLEDGEMENTS

The project is supported by the Academy of Finland (project number 326291) and the University of Oulu Academy of Finland Profi5 on Digihealth. This work also was supported in part by the Ministry of Education and Culture, Finland (OKM/20/626/2022). Moreover, SA was supported by the Kermanshah University of Technology, Iran, under grant number S/P/F/5.

REFERENCES

Ahmadian, M., Ahmadi, M., and Ahmadian, S. (2022a). A reliable deep representation learning to improve trust-aware recommendation systems. *Expert Systems with Applications*, 197:116697.

Ahmadian, S., Joorabloo, N., Jalili, M., and Ahmadian, M. (2022b). Alleviating data sparsity problem in time-aware recommender systems using a reliable rating profile enrichment approach. *Expert Systems with Applications*, 187:115849.

Asani, E., Vahdat-Nejad, H., and Sadri, J. (2021). Restaurant recommender system based on sentiment analysis. *Machine Learning with Applications*, 6:100114.

Bianchini, D., De Antonellis, V., De Franceschi, N., and Melchiori, M. (2017). Prefer: A prescription-based food recommender system. *Computer Standards & Interfaces*, 54:64–75.

Chavan, P., Thoms, B., and Isaacs, J. (2021). A recommender system for healthy food choices: Building a hybrid model for recipe recommendations using big data sets. In *Proceedings of the 54th Hawaii International Conference on System Sciences*, page 3774.

Chen, M., Jia, X., Gorbonos, E., Hoang, C. T., Yu, X., and Liu, Y. (2020). Eating healthier: Exploring nutrition information for healthier recipe recommendation. *Information Processing & Management*, 57(6):102051.

Elsweiler, D., Trattner, C., and Harvey, M. (2017). Exploiting food choice biases for healthier recipe recommendation. In *Proceedings of the 40th international acm sigir conference on research and development in information retrieval*, pages 575–584.

Forouzandeh, S. and Aghdam, A. R. (2019). Health recommender system in social networks: A case of facebook. *Webology*, 16(1).

Gao, X., Feng, F., He, X., Huang, H., Guan, X., Feng, C., Ming, Z., and Chua, T.-S. (2019). Hierarchical attention network for visually-aware food recommendation. *IEEE Transactions on Multimedia*, 22(6):1647–1659.

Gao, X., Feng, F., Huang, H., Mao, X.-L., Lan, T., and Chi, Z. (2022). Food recommendation with graph convolutional network. *Information Sciences*, 584:170–183.

Ghosh, P., Bhattacharjee, D., and Nasipuri, M. (2021). Dynamic diet planner: A personal diet recommender system based on daily activity and physical condition. *IRBM*, 42(6):442–456.

Lawlor, D. A. and Pearce, N. (2013). The vienna declaration on nutrition and non-communicable diseases.

Meng, L., Feng, F., He, X., Gao, X., and Chua, T.-S. (2020). Heterogeneous fusion of semantic and collaborative information for visually-aware food recommendation. In *Proceedings of the 28th ACM International Conference on Multimedia*, pages 3460–3468.

Organization, W. H. et al. (2007). Population nutrient intake goals for preventing diet-related chronic diseases. *http://www. who. int/nutrition/topics/*.

Organization, W. H. et al. (2014). *Global status report on noncommunicable diseases 2014*. Number WHO/NMH/NVI/15.1. World Health Organization.

Rostami, M. and Oussalah, M. (2022a). Cancer prediction using graph-based gene selection and explainable classifier. *Finnish Journal of eHealth and eWelfare*, 14(1):61–78.

Rostami, M. and Oussalah, M. (2022b). A novel explainable covid-19 diagnosis method by integration of feature selection with random forest. *Informatics in Medicine Unlocked*, 30:100941.

Shabanabegum, S., Anusha, P., Seethalakshmi, E., Shunmugam, M., Vadivukkarasi, K., and Vijayakumar, P. (2020). Iot enabled food recommender with nir system. *Materials Today: Proceedings*.

Shaikh, S. G., Suresh Kumar, B., and Narang, G. (2022). Recommender system for health care analysis using machine learning technique: a review. *Theoretical Issues in Ergonomics Science*, pages 1–30.

Tian, Y., Zhang, C., Metoyer, R., and Chawla, N. V. (2021). Recipe recommendation with hierarchical graph attention network. *Frontiers in Big Data*, 4:1–13.

Wang, W., Duan, L.-Y., Jiang, H., Jing, P., Song, X., and Nie, L. (2021). Market2dish: Health-aware food recommendation. *ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM)*, 17(1):1–19.